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Original Article

Artificial Neural Networks for Predicting Natural Frequencies of Concrete Gravity Dams: A Moroccan Case Study

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Abstract *- Predicting the seismic behavior of concrete gravity dams is a critical challenge in earthquake engineering. This Study investigates the potential of Artificial Neural Networks (ANNs) in predicting the natural frequency of concrete gravity dams based on their geometric and mechanical properties. A dataset of 320 numerical simulations was developed to train and evaluate different artificial neural network architectures. The results indicate that simple neural networks with one or two hidden layers provide strong predictive capabilities for predicting the fundamental frequency, depending on the number of neurons in each layer. However, the proposed approach does not yet incorporate all the factors that may influence the seismic response of a dam, such as hydrodynamic forces and realistic seismic input. Future research could integrate nonlinear modeling and realistic earthquake excitations to validate and enhance the trends identified in this Study. These findings underscore the potential of data-driven modeling, such as neural networks, to evaluate seismic vulnerability, especially for massive concrete structures.*

Keywords *- Artificial Neural Networks, Concrete dams, Frequency prediction, Numerical modeling, Dynamic behavior.*

1. Introduction

Since the early 21st century, the socio-economic dynamics of water utilization in the Kingdom of Morocco, a country characterized by a semi-arid climate, have been exposed to significant changes caused by urban expansion, demographic pressure, and the groundwater resources [1]. As a result, the development of dam infrastructure has been historically considered a priority in Morocco's water policy. [2]. Furthermore, Morocco has a total of 140 large dams with a combined storage capacity exceeding several billion cubic meters. Among them, 13 are reserved for water transfer, with a total length of 1,100 km, a flow capacity of 200 m³/s, and an annual transfer volume of 2.5 billion m³ [3]. Moreover, Morocco is recognized as a leader in large-scale hydraulic, with the largest irrigated areas in the Maghreb, some exceeding 100,000 hectares, and more than 100 large dams [2]. It is worth emphasizing that the construction of dams has been employed since ancient times by various civilizations as a way to manage and utilize water resources [4]. By definition, dams are considered engineered structures designed to regulate water flow. They accomplish this objective by capturing and controlling its volume and release, thereby adjusting the magnitude and timing of downstream movement [5]. Consequently, they channel water flow, which enables the creation of a reservoir with the necessary water head. In addition, they regulate the downstream discharge [6]. Moreover, dams constructed on rivers fulfil multiple functions, including but not limited to the provision of drinking water, hydroelectric power generation, agricultural irrigation, industrial water supply, flood management, fisheries development, sediment control, and recreational activities [7]. From the conceptual and technical perspectives, the configuration and materials employed in the dam's construction are based on the characteristics of the project site, the particular design, the operational requirements and the prevailing geological conditions [6]. As a result, dams can be classified into various types, including embankment dams: earth-fill dams and rockfill dams and rigid dams: comprising gravity dams, rolled compacted concrete dams, arch dams, and buttress dams [7].

Considering the dangerous impacts related to the high seismic risk, especially in dam structures, it is imperative to develop a comprehensive understanding of their dynamic behavior and the factors that influence it. This knowledge is essential for limiting the risk of unexpected structural responses, ensuring the safety and stability of these critical infrastructure elements [23]. It has been demonstrated that parameters such as natural frequency, vibration modes, and structure–fluid–soil interactions significantly influence the reliability of simulations and seismic safety of dams [24]. By definition, the natural frequency of a structure is the inherent rate at which a structure vibrates on its own after an initial disturbance, without the influence of damping or sustained external excitation [24]. It essentially depends on the overall mass and stiffness of the structure [24]. In the context of gravity dams, this frequency is crucial. Indeed, in the event that it aligns with the natural frequency of a local earthquake, resonance may be triggered, substantially amplifying dynamic loads [25].

Additionally, modal analysis identifies a system's natural frequencies and associated mode shapes by solving an eigenvalue problem based on the differential equations of motion [30]. These mode shapes represent the distinct vibration behaviors of the structure [26]. This analysis is generally conducted through the application of the finite element method, which is a technique that facilitates the construction of complex models of the dam's geometry, along with its interactions with the rock foundation and the reservoir fluid [27].

The Finite Element Method (FEM) is defined as a numerical technique that subdivides complex structures into discrete elements in order to simulate mechanical behaviors [28]. However, this method is not without limitations, particularly the required intensive mesh resolution, which increases processing time and computational costs. [29]. Furthermore, variability in the mechanical properties of materials significantly affects the accuracy of the results generated from finite element models [30]. Additionally, the simplification of modeling assumptions is a common practice in this type of analysis, particularly in the context of linear material behavior. However, this approach can impede the efficacy of the finite element method in capturing nonlinear seismic responses. [31] It should be added that the accurate interpretation of computational results requires specialized expertise and empirical validation to ensure their credibility and precision [32]. Consequently, these limitations emphasize the necessity of adopting hybrid or complementary approaches to accurately evaluate the dam’s behavior under dynamic conditions [33]. In light of these constraints, Artificial Neural Networks (ANNs) have emerged as a promising alternative to conventional methods, through facilitating the accurate prediction of dynamic behaviors with considerably reduced computational effort [34, 35].

In recent years, Artificial Neural Networks (ANNs) have emerged as viable alternatives for structural prediction tasks due to their capacity to model complex nonlinear interactions and manage uncertain, noisy or missing data [36, 37]. This is due to the fact that ANNs have proven considerable potential in civil engineering applications, including material strength prediction, structural damage assessment, and dynamic performance analysis. [38, 39]. However, despite their proven potential, few studies have focused on the use of ANNs to estimate dynamic characteristics of concrete gravity dams, such as the natural frequency [40]. Indeed, in the Moroccan context, the paucity of research addressing these issues is significant, given the country's particular construction norms, complex geotechnical conditions, and seismic sensitivity [41].

To address this Knowledge gap, this research aims to develop an artificial neural network model to accurately predict the natural frequencies of several concrete gravity dams in Morocco. These models are trained using synthetic geometric and dynamic data derived from conventional Finite Element Method (FEM) simulations. Consequently, the main objective of this Study is to evaluate the efficacy of ANN-based approaches in effectively surmounting some of the critical FEM limitations, including the susceptibility to the quality of mesh, the high computational cost and the stringent boundary condition requirements. In addition, by comparing ANN results with conventional FEM outcomes, the Study also seeks to assess the capability and adaptability of neural networks to provide a more flexible and efficient tool for dynamic analysis in dam engineering, particularly in capturing complex dam–foundation–reservoir interactions.

2. Artificial Neural Networks

2.1. Definition of ANN

Inspired by the structural and functional principles of the human brain, Artificial Neural Networks (ANNs) represent a class of machine learning algorithms [8]. As seen in Figure 1, ANNs are composed of a large number of interconnected processing elements that are organized into three essential layers: the input, hidden and output layers [9]. These entities function as computational structures that iteratively adjust their parameters to model the fundamental relationship between input and output parameters [10]. Moreover, each fundamental processing unit is responsible for receiving information at the input nodes, executing internal computation, and generating a result at the output nodes [11]. Furthermore, neural networks demonstrate high predictive capacities when trained on large datasets comprising several prior cases [12].

2.2. Working of an ANN

In the context of neural networks, each connection is assigned a weight, and each neuron is characterized by a threshold value and an activation function that determine its output [13]. As the simplest ANN model introduced by Rosenblatt, the perceptron represents the most basic type of artificial neural network, in which inputs are individually weighted and combined through a mathematical operation known as the neuron activation function [10]. The activation function is operational provided that each input has a positive or negative weight. The magnitude of this weight determines the intensity of the signal transmitted through the connection [13].

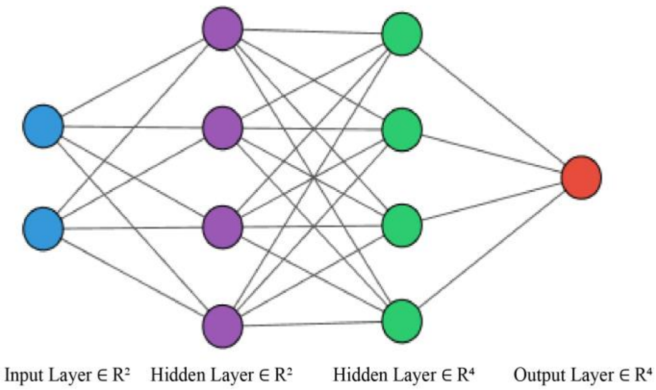

Fig. 1 Schematic representation of an artificial neural network

2.3. Types of Neural Network

In the broad Sense, artificial neural networks are considered computational models that emulate the functioning of the human brain. These networks have the capacity to provide effective solutions to a wide range of complex problems in various application domains [12]. Moreover, among the most neural architectures explored in depth, feedforward networks and feedback (recurrent) networks are particularly prominent [13].

2.3.1. Feed Forward Neural Network

This fundamental Artificial Neural Network (ANN) architecture is frequently used for typical recurring and analysis tasks [14]. It is classified as a multilayer, fully connected hierarchical network, composed of an input layer, one or more hidden layers, and an output layer [15]. Furthermore, as seen in Figure 2, this network is strictly unidirectional and feedforward, with the absence of connections or recurrent loops [13]. In addition, the transmission of data occurs in a unidirectional manner from the input layer to the output layer [12]. Each unit processes incoming signals from the preceding layer, applying a weight to every input data element depending on the strength of its connection [13].

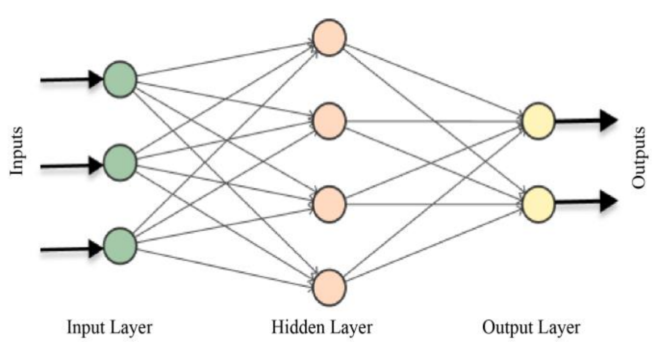

Fig. 2 Structure of a typical feedforward neural network

2.3.2. Recurrent Neural Network

A Recurrent Neural Network (RNN) is a machine learning algorithm that processes data by retraining the output from previous layers and feeding it back as input, enabling the network to predict the outcome of the layer [12]. Indeed, the implementation of recurrent connections within feedback networks facilitates the communication of information in both forward and reverse directions [15]. From an application perspective, RNNs have been applied in several domains, including language modeling, image processing, and systems in which characters are added sequentially to text [14]. As seen in Figure 3.

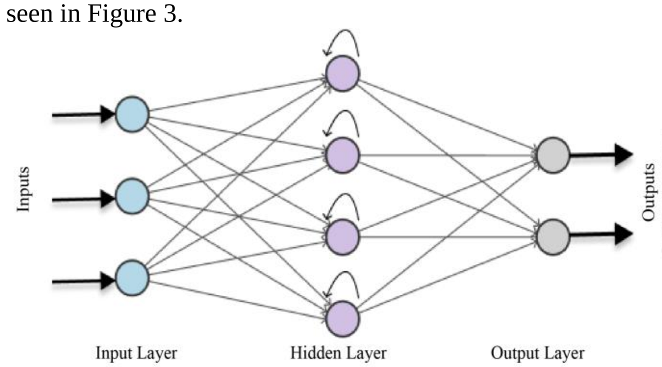

Fig. 3 Structure of a typical recurrent neural network

2.4. Advantages of an ANN

The main advantage of using a neural network in any of the aforementioned issues is its remarkable capacity for learning and its resilience to minor perturbations [13]. In fact, ANNs have demonstrated an ability to learn and model non-linear and complicated interactions, a capacity that is particularly critical in contexts where real-life situations frequently exhibit such non-linear and complex relationships between input and output parameters [16]. Moreover, neural networks, with their significant ability to derive meaning from complicated or imprecise data, render them a suitable instrument for the extraction of patterns and the detection of trends [14].

2.5. Applications in the Civil Engineering Field

In the civil engineering field, artificial neural networks have proven efficacy in solving complex problems and predictive modeling. In fact, in their work, Zhang et al. introduce PhyCNN, a convolutional neural network improved by physical constraints. This innovation reduces data requirements, thereby enhancing dynamic response prediction [17]. Furthermore, Yasin applied an ANN to predict dynamic properties of concrete, providing high accuracy and efficiency [19]. Iqbal et al. developed an artificial neural network model that accurately predicts the axial strain of Fibre-Reinforced Polymer (FRP)-confined concrete. This model surpasses conventional empirical methods [18]. In addition, Kaushik et al. also presented a comprehensive overview of artificial neural networks in the construction field, offering useful insights into their practical applications and future research direction [20]. Moreover, Ahmed et al. thoroughly reviewed artificial neural networks' capacity to improve viability in the construction industry across environmental, economic, and social dimensions [21].

3. Methods

Ensuring structural stability during seismic events is critically important in civil engineering practice. Indeed, earthquakes are defined as sudden events that cause high vibrations. These vibrations can potentially lead to structural failure or collapse [22].

Dams are defined as critical infrastructures that require thorough technical design and execution. These structures are vulnerable to extreme damage or failure in the event of seismic activity. Therefore, this Study adopts a numerical approach to simulate various gravity dam configurations with varied geometric parameters (length, height), and mechanical properties (elastic modulus, density, and Poisson's ratio).

Consequently, a comprehensive approach including numerical simulations and artificial intelligence was implemented to accurately predict the natural frequencies of concrete gravity dams in Morocco. In the first step, simulated data were obtained using the Finite Element Method (FEM). These simulations included varying the geometric and mechanical properties of dams in Morocco. Dynamic simulation software was used to conduct these simulations. As illustrated in Figures 4 and 5, the only applied load is the self-weight of the dam-foundation structures without any external forces or dynamic effects.

Subsequently, these data were used to train Artificial Neural Network (ANN) models, aiming to capture the nonlinear interactions between input parameters (dimensions, elastic modulus, density) and the natural frequency results. Therefore, various neural network architectures were explored to identify the configuration that provides the most accurate results.

In addition, to evaluate the model's reliability, cross-validation was employed, and the ANN predictions were consistently compared to FEM results. This approach aims to evaluate the effectiveness of neural networks as a reliable, robust substitute to conventional dynamic simulations of dam structures.

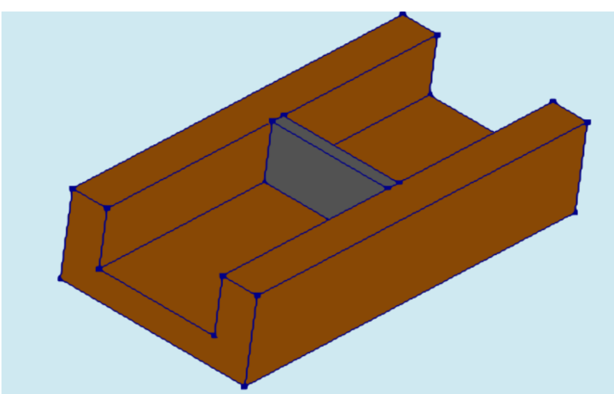

Fig. 4 Basic model of dam-foundation structure

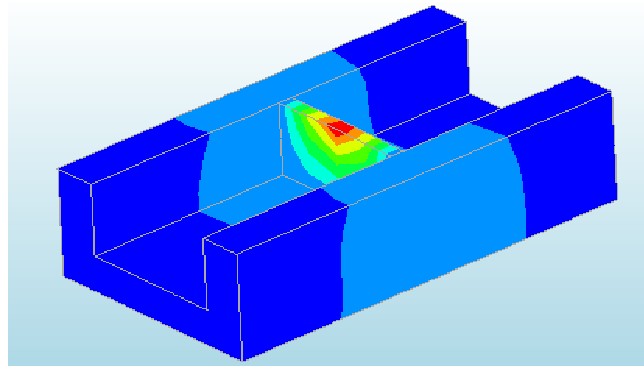

Fig. 5 Simulated behavior of the dam–foundation structure

In order to build a reliable dataset for training the predictive model, numerical simulations were conducted using a dynamic simulation software based on the Finite Element Method (FEM). This method is widely acknowledged for its proven accuracy in evaluating complex structures in civil engineering applications. The simulations were based on models of ten concrete gravity dams in Morocco. These were chosen to represent a wide range of geometric and mechanical characteristics, such as concrete and rock foundations. Geometric parameters (height, length) and mechanical characteristics (elastic modulus, density, Poisson's ratio) were systematically varied to represent a variety of structural configurations. For each model, a modal analysis was executed to extract the structure's natural frequency (Dam-Foundation), seeking to evaluate the structure's dynamic behavior, using FEM-based software. This approach depends on solving the structural free vibration equation, enabling the identification of natural modes without applying external dynamic loads [3]. In the present work, the focus is specifically on the first vibration mode of each dam's configuration. Moreover, the generation of natural frequency data for each configuration was achieved through 320 distinct simulations. Subsequently, the Artificial Neural Network (ANN) models were implemented in later phases.

In the strict Sense, a neural network model's predictive accuracy is essentially dependent on a suitable choice of input variables. Indeed, the selected parameters for this Study include geometric variables that directly affect the dynamic response of dams (height, length) and mechanical characteristics (elastic modulus, mass density, Poisson's ratio) [2]. Furthermore, input data were normalized within the interval [-1, 1] to ensure efficient convergence throughout the model training.

The present Study introduces an Artificial Neural Network (ANN) architecture designed as a Multi-Layer Perceptron (MLP) with a feedforward structure using MATLAB and its Neural Network Toolbox. Furthermore, the network is organized with three types of layers: the input layer receives seven normalized parameters, including the dam's height and length, the elastic modulus of the dam and foundation, the material density of the dam and foundation, and the Poisson's ratio of the foundation. As illustrated in Table 1, implementing one, two or three hidden layers was executed, with the number of neurons being modified within the range of 5 to 40. However, the output layer includes a single neuron that generated a continuous value of the fundamental natural frequency for each tested configuration. For the hidden layers, the hyperbolic tangent sigmoid function (tanh) was selected as the activation function. Moreover, a linear activation function (purelin) was implemented in the output layer to produce continuous predictions. In the context of this numerical simulation, 320 distinct configurations were generated, with 224 (70%) allocated for model training, 48 (15%) designated for validation, and the remaining 48 (15%) allocated for testing.

Table 1. The following represent the configurations of neural networks employed in this study

Case	ANN Architecture	Activation Function	Training Algorithm	Description
1	Feedforward [5]	tansig	trainlm	1 hidden layer with 5 neurons
2	Feedforward [30]	tansig	trainlm	1 hidden layer with 30 neurons
3	Feedforward [10, 5]	tansig	trainlm	2 hidden layers with 10 and 5 neurons
4	Feedforward [30, 15]	tansig	trainlm	2 hidden layers with 30 and 15 neurons
5	Feedforward [10, 8, 5]	tansig	trainlm	3 hidden layers with 10, 8 and 5 neurons
6	Feedforward [40, 30, 20]	tansig	trainlm	3 hidden layers with 40, 30 and 20 neurons

In the following step, the network is trained using the Levenberg–Marquardt algorithm (trainlm), which is particularly appropriate for moderate-sized datasets and for modeling intricate nonlinear system behaviors with minimal error. Furthermore, the model's performance was evaluated using multiple metrics, including the coefficient of determination. R^2 and the final Mean Squared Error (MSE). In the first place, the Mean-Squared Error (MSE) is defined as a statistical measure that calculates the average of the squared differences between predicted and observed values. Indeed, a lower MSE indicates a higher degree of model accuracy.

In the second place, the coefficient of determination (R^2) is a statistical measure of how well a model explains the variability in a dataset. A value close to 1 indicates a strong fit between the model and the data. In practice, a low MSE combined with a high R^2 reflects reliable model performance. The subsequent flowchart (Figure 6) illustrates the successive steps that were followed in the development of this Study. Table 2 presents a comprehensive synthesis of all input and output data for the ten structure cases (dam–foundation systems).

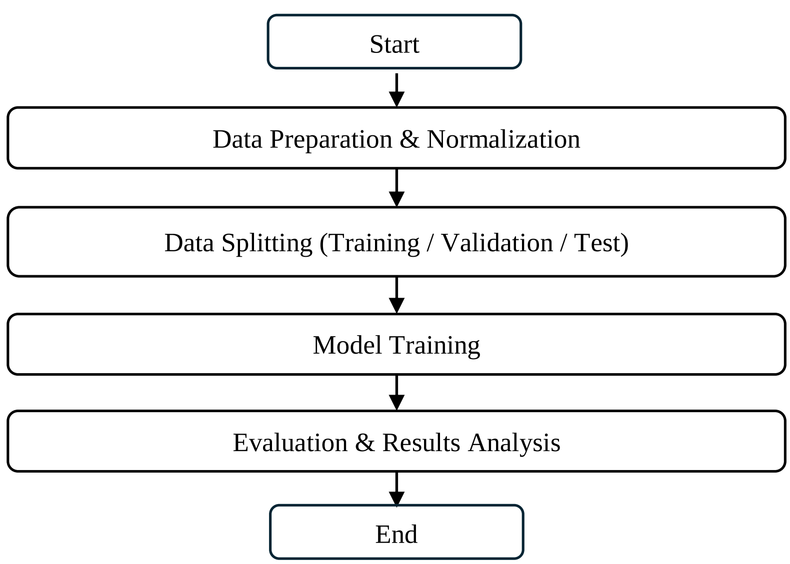

Fig. 6 Structured process for conducting the experimental study

Table 2. Summary of input and output data for the dam–foundation structure cases

Parameter / Structure	Input Data							Output Data
	Dam				Foundation			Natural frequency
	L (m)	H (m)	E (GPa) (Variations)	ρ (Kg/m^3) (Variations)	E (GPa) (Variations)	ϑ (Variations)	ρ (Kg/m^3) (Variations)	F (Hz) (range)
Structure 1	100	60	25/32	2300/2500	50/60/70/100	0.2/0.25	2600/2700/2800/3000	[6.7528-9.3793]
Structure 2	230	50	25/35	2300/2500	50/60/70/100	0.2/0.25	2600/2700/2800/3000	[6.4886-8.9417]
Structure 3	240	60	25/35	2300/2500	50/60/70/100	0.2/0.25	2600/2700/2800/3000	[5.8575-7.6797]
Structure 4	280	64	25/35	2300/2500	50/60/70/100	0.2/0.25	2600/2700/2800/3000	[5.5691-6.929]
Structure 5	290	133	25/35	2300/2500	50/60/70/100	0.2/0.25	2600/2700/2800/3000	[1.9482-4.9257]
Structure 6	210	29	25/35	2300/2500	50/60/70/100	0.2/0.25	2600/2700/2800/3000	[7.1807-9.8944]
Structure 7	260	67	25/35	2300/2500	50/60/70/100	0.2/0.25	2600/2700/2800/3000	[5.9762-8.1268]
Structure 8	200	45	25/35	2300/2500	50/60/70/100	0.2/0.25	2600/2700/2800/3000	[6.8811-9.3844]
Structure 9	260	64	25/35	2300/2500	50/60/70/100	0.2/0.25	2600/2700/2800/3000	[5.4044-6.6635]
Structure 10	120	43	25/35	2300/2500	50/60/70/100	0.2/0.25	2600/2700/2800/3000	[7.0363-9.646]

Table 3. MSE and R^2 values for different neural network configurations

Case	Typology of Artificial Neural Networks	Training Algorithm	Activation function	MSE	R^2
1	Feedforward [5]	trainlm	tansig	0.13466	0.95061
2	Feedforward [10]	trainlm	tansig	0.13822	0.9493
3	Feedforward [15]	trainlm	tansig	0.12617	0.95372
4	Feedforward [20]	trainlm	tansig	0.15042	0.94483
5	Feedforward [30]	trainlm	tansig	0.16876	0.9381
6	Feedforward [10, 5]	trainlm	tansig	0.17373	0.93628
7	Feedforward [15, 10]	trainlm	tansig	0.15151	0.94442
8	Feedforward [20, 10]	trainlm	tansig	0.15712	0.94237
9	Feedforward [25, 15]	trainlm	tansig	0.14263	0.94768
10	Feedforward [30, 15]	trainlm	tansig	0.16383	0.93991
11	Feedforward [10, 8, 5]	trainlm	tansig	0.20662	0.92421
12	Feedforward [15, 10, 5]	trainlm	tansig	0.24668	0.90951
13	Feedforward [20, 15, 10]	trainlm	tansig	0.21352	0.92168
14	Feedforward [30, 20, 10]	trainlm	tansig	0.15349	0.9437
15	Feedforward [40, 30, 20]	trainlm	tansig	0.6435	0.76396

4. Results and Discussion

The Study's next step involves varying the number of neurons and layers in the neural network to ascertain their impact on prediction performance. Indeed, the performance of various Artificial Neural Network (ANN) architectures was assessed using two fundamental metrics: The Mean Squared Error (MSE) and the coefficient of determination (R^2). As illustrated in Table 1, a total of fifteen feedforward Artificial Neural Network (ANN) architectures were examined. It is important to note that all of the architectures were trained with the Levenberg-Marquardt (trainlm) algorithm and employed the tansig activation function (hyperbolic tangent sigmoid). In addition, the Architectural differences manifest in the quantity and dimensions of hidden layers. Moreover, the performance evaluation is conducted using Mean Squared Error (MSE) and the determination coefficient (R^2).

4.1. Neural Network Architecture and Prediction Performance

Considering the generated results, the first five cases correspond to architectures with a single hidden layer and an increasing number of neurons, ranging from 5 to 30. It is observed that the configuration with one hidden layer of 15 neurons (Case 3) exhibited the optimal predictive performance among all tested and evaluated neural network models. This is due to a minimal prediction error (MSE = 0.1262) and an elevated coefficient of determination (R^2 = 0.9537). Consequently, this architecture appears to offer an optimal compromise between model complexity and generalization ability without leading to overfitting caused by excessive network depth or size. It can also be observed that a minor decrease in performance occurred when the number of neurons is lower or higher than this value (15).

For Case 1 with 5 neurons, the MSE is 0.13466 and R^2 is 0.95061. These findings indicate that this model exhibits satisfactory performance. However, its efficacy is less compared to the 15-neuron (case 3). Furthermore, the configuration with 30 neurons (case 5) demonstrates a considerable decline in performance (MSE = 0.16876, R^2 = 0.93810), which potentially reflects slight overfitting or an excessively complex architecture. These results demonstrate that a single hidden layer with a moderate number of neurons can provide robust predictive performance. By contrast, increasing the number of neurons from 5 to 30 negatively impacted performance. In summary, this finding highlights the efficacy of low-depth architectures in addressing complex problems.

As shown in Figure 7, for the Cas 3 with one hidden layer of 15 neurons, which demonstrated the optimal performance, the predicted values of natural frequencies are closely aligned with the original values generated from FEM along the identity diagonal. Similarly, as illustrated in Figure 8, the training, testing, and validation converge smoothly and remain closely parallel for the same Case. These observations suggest that the model in Case 3 demonstrates high accuracy in predicting the real values of natural frequencies.

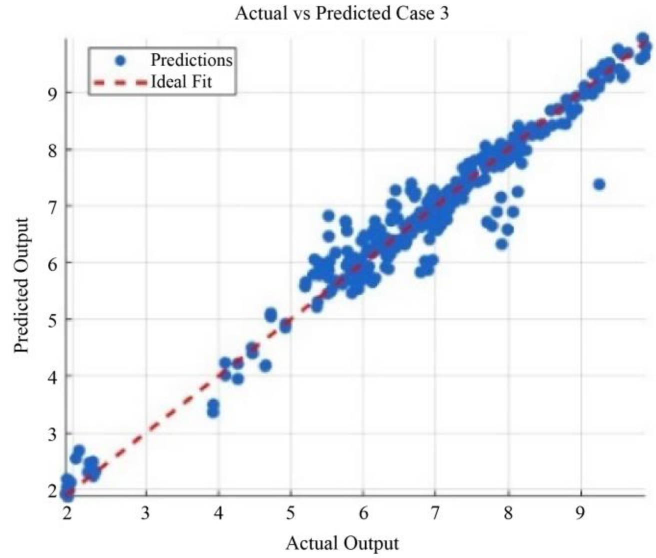

Fig. 7 Scatter Plot of predicted against actual values of natural frequencies for case 3

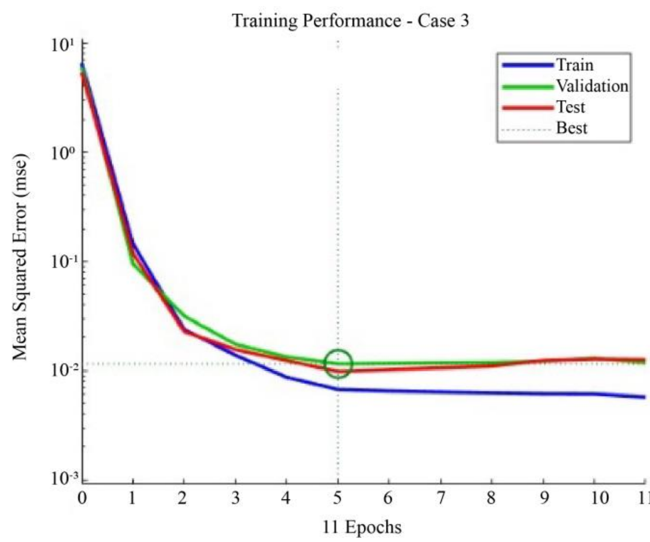

Fig. 8 Evolution of loss during training, validation, and testing for case 3

The two - hidden - layer architectures include configurations such as [10, 5], [15, 10], and up to [30, 15]. These architectures generally demonstrate lower performance in comparison to the optimal single-layer architecture (Case 3). Case 9 yields the best performance in this category, with an MSE of 0.14263 and an R^2 of 0.94768. On its part, case 6 ([10, 5]) attains a higher MSE of 0.17373 and decreased R^2 of 0.93628, indicating reduced performance. In this context, incorporating an additional hidden layer does not ensure superior performance. This finding suggests that increased complexity may not necessarily lead to better outcomes.

Finally, the three-hidden-layer architectures (Cases 11 to 15) are more complex configurations. These deeper models generally perform less than the optimal one-hidden-layer configuration (case 3). Moreover, among the three-hidden-layer models, the [30,20,10] architecture (Case 14) achieved the best-performing configuration (R^2 = 0.94370, MSE = 0.15349), comparable to the top results of two-layer models.

Furthermore, it is observed that the performance deterioration becomes more significant: The range of MSE extends from 0.15349 (case 14) to a remarkably maximum of 0.64350 (case 15). In this respect, R^2 values decrease as well, ranging from 0.92421 to 0.76396, which is significantly less than in preceding cases.

To summarise, the analysis of the results reveals that the neural network architecture significantly impacts the model's performance. Subsequently, the optimal balance between complexity and performance was achieved by a single hidden layer architecture of 15 neurons, with the minimal MSE and maximal R^2. However, increasing the number of neurons or employing deeper architectures did not necessarily yield enhanced outcomes.

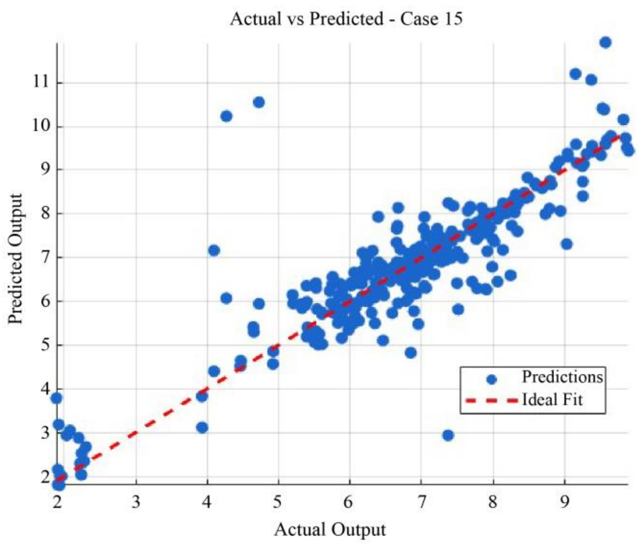

Fig. 9 Scatter plot of predicted against actual values for cas 15

Regarding the graphical outputs generated in MATLAB, the scatter plot in Figure 9 shows a significant discrepancy between the predicted and actual values compared to the identity diagonal, suggesting that the model in Case 15, with the most complex and deepest configuration, may not accurately predict the true values.

Furthermore, as shown in Figure 10, in Case 15, the training curve exhibits a consistent decrease, while the test and validation curves reach a state of stability or even increase. This phenomenon indicates a potential occurrence of overfitting, which can compromise the model's ability to generalize effectively.

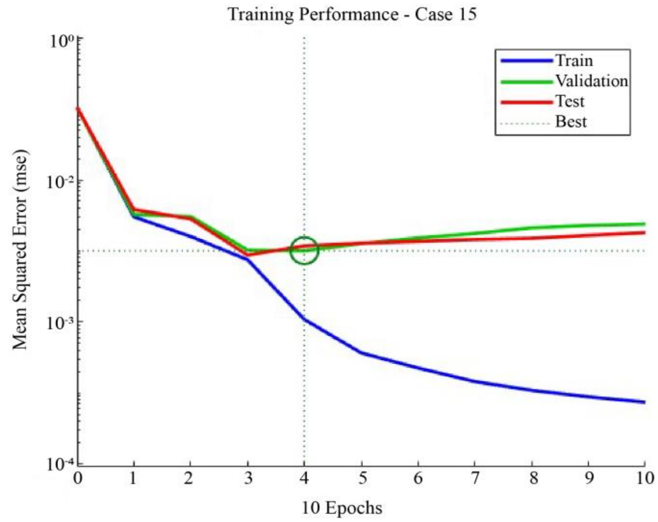

Fig. 10 Evolution of loss during training, validation, and testing for case 15

As shown in Figure 11, the diagram presents a visual summary of the performance indicators R^2 (coefficient of determination) and MSE (Mean Squared Error) for different network depths (number of hidden layers) and complexities (number of neurons per layer) across the neural networks evaluated in this Study.

4.2. Comparative Performance Analysis with Related Studies

This section presents a comparative assessment of the performance of the proposed ANN models compared to similar simulation-based studies. Indeed, the present research focused on predicting the natural frequencies of concrete gravity dams based on simulated MEF datasets.

This Study achieved high predictive accuracy, with an MSE of 0.12617 and an R^2 of 0.95372. These results reflect high predictive precision and a substantial correlation between observed and predicted values.

Similarly, El Abidi et al. (2025) present a study aiming to predict Moroccan pavement's performance, using Artificial Neural Networks; they achieve an R^2 of 0.8156 and MSE of 0.0037. Moreover, El Mkhalet and Lamdouar (2025) in their research about the prediction of seismic displacements have reported that the Random Forest approach achieves a significantly lower MSE ($\sim 9.9 \times 10^{-8}$) compared to traditional artificial neural networks.

Furthermore, Salhi et al. (2025) studied the prediction of the Structural reliability index. Achieve an R^2 of 0.853408 with an MSE of 0.0037. On their part, Alqatawna (2024), Onyelowe et al. (2021), and Onyelowe et al.(2023) demonstrate excellent predictive capabilities in their field of application.

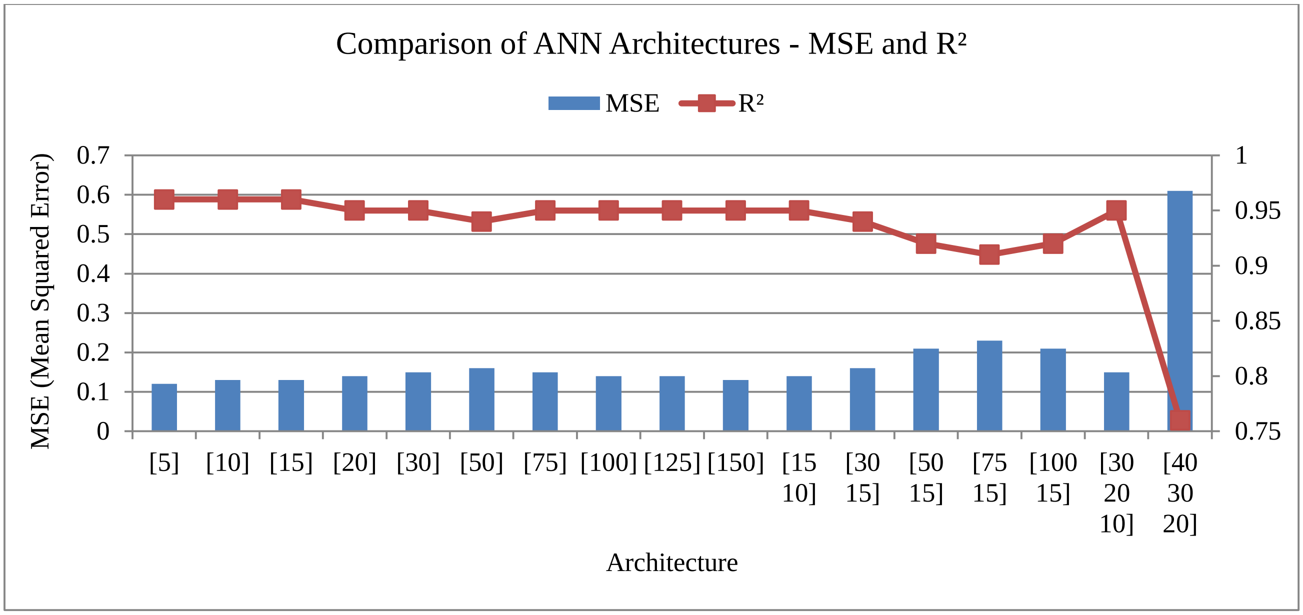

Fig. 11 Evolution of MSE and R^2 as functions of both the network depth and the complexity across the neural networks evaluated

In the realm of architectural design, the present model is characterized by its simplicity, with a single hidden layer of 15 neurons. This configuration is designed to minimize computational costs, enabling an effective balance between execution speed and accuracy. In contrast, Salhi et al. (2025) propose a more complex architectural design comprising three hidden layers, each with 11, 12 and 13 neurons. However, these architectures come with considerably higher algorithmic complexity and computational cost.

In summary, the present work effectively balances predictive accuracy, computational efficiency, and implementation simplicity. These results confirm the relevance of this model, which achieved an accuracy that is comparable to that reported in the other studies.

Table. 4 Comparative overview of the present work and other similar research, highlighting objectives, network architectures, training data, and achieved accuracies

Study / Case	Objective	Optimal Architecture	Training Algorithm	Activation Function	Training Data	Data to Predict	Optimal performance (MSE / R^2)
The present Study	Predict dynamic properties of concrete gravity dams.	1 layer with 15 neurons.	Levenberg–Marquardt.	tansig	Simulated geometric and mechanical data. (320 case)	Natural frequency of concrete gravity dams in Morocco.	MSE = 0.12617 R^2 = 0.95372.
M. El Mkhalet & N. Lamdouar (2025) [42]	Comparison between Random Forests and Artificial Neural Networks to Predict the seismic displacements of a Single-Degree-Of-Freedom (SDOF) structure subjected to random seismic excitations.	ANN: 2 layers / 10 neurons each. RF: 50 trees.	Levenberg-Marquardt for ANN.	Not specified.	Data simulated using the Newmark-Beta method.	Seismic displacements.	MSE = 0.086594.

O. El Abidi et al. (2025) [43]	Predict the performance of Moroccan pavements using Artificial Neural Networks.	ANN with 1 hidden layer and 5 neurons	Levenberg-Marquardt (trainlm).	Tansig is for the hidden layer, and purelin is for the output layer.	Degradation data from an automated vehicle on Morocco's National Highway N1.	The Pavement Condition Index (PCI)	MSE = 0.0037 R^2 = 0.8156
C. Salhi et al. (2025) [44]	Assess the reliability of Unstabilized Rammed Earth (URE) structures under wind pressure.	ANN with 3 hidden layers (11, 12, and 13 neurons).	Levenberg-Marquardt.	ReLU	Dataset generated by Monte Carlo Simulation	Structural reliability index.	MSE = 0.023462 R^2 = 0.853408
A. Alqatawna (2024) [45]	Predict the road traffic accidents (RTAs) on Spanish highways by Utilizing Artificial Neural Networks (ANNs)	ANN with 1 hidden layer and 9 neurons	Levenberg-Marquardt	Sigmoid activation	Dataset generated from road traffic accidents that occurred from 2014 to 2017.	The number of road traffic accidents on Spanish highways.	MSE = 93.887 R^2 = 0.9992
Onyelowe et al. (2021) [46]	Assess an expansive clay's consistency, compressibility, and strength characteristics using Artificial Neural Network and Fuzzy Logic models.	ANN with 1 hidden layer and 6 neurons	Levenberg-Marquardt	Sigmoid activation	The proportions of the soil mix, with their compaction and consistency limit properties	The strength responses of the soil mix	MSE = 0.1726 R^2 = 0.9983
V.V.Tuan (2023) [47]	Predict the compressive strength and slump values of concrete samples using. Artificial Neural Network (ANN) and Decision Tree (DT) methods	ANN with a single hidden layer and 180 neurons	A multi-layer feedforward with backpropagation learning algorithm was used.	ReLU and tanh activation functions	Experimental data generated from a previous research project	compressive strength and slump values of concrete samples	Compressive strength : MSE = 0.154 R^2 = 0.991 and Slump : MSE = 0.109 R^2 = 0.997

4.3. Contribution of the Study

This Study thoroughly evaluates neural network architectures with one, two, and three hidden layers, analyzing how varying the number of neurons per layer impacts predictive performance. Moreover, it identifies configurations that achieve optimal balance between accuracy (R^2) and error (MSE), revealing that certain Low-depth networks, such as [15] or [15, 25,], can outperform more complex architectures. Additionally, the findings highlight the limitations of deeper networks, such as [20, 30, 40], which exhibit a tendency to overfit the data. Using standardized evaluation metrics (R^2, MSE) and a comparative approach on a fixed dataset, this Study establishes a reproducible methodology for evaluating and optimizing neural network prediction performance of some mechanical properties, such as natural frequency in a dam configuration.

5. Conclusion

To conclude, this Study aimed to apply Artificial Neural Networks (ANNs) to predict the natural frequency of concrete gravity dams based on their geometric and mechanical properties. In fact, the present Study investigated the impact of these variables on the structures' seismic behavior and determined architectural configurations that provide an optimal compromise between accuracy and generalization capability, particularly in the modeling of massive structures. Moreover, among all tested configurations, the Feedforward [15] architecture employing the Levenberg–Marquardt training approach with the tansig activation function delivered the Most Accurate Results (MSE = 0.12617; R^2 = 0.95372), signifying an excellent agreement between predicted and measured values. It should also be noted that a moderate increase in neuron count enhanced the model's accuracy. However, exceeding a critical limit led to overfitting, reducing its generalization ability.

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